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Real-Time Speech Enhancement on Edge Devices Using Optimized Deep Learning Models

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ABSTRACT

With edge computing increasing becoming a popular implementation for real-time processing and storing data, voice driven applications need effective and lightweight Speech Enhancement Systems to meet real-time processing requirement on constrained hardware platforms. In this work, we propose a deep learning – based speech enhancement framework optimized for the real – time improvement of speech quality on the edge. The system proposed in this thesis contains a convolutional recurrent neural network (CRNN) architecture with pruning and quantization techniques that reduce complexity of the model without reducing performance. The experiments were conducted extensively across the TIMIT and DNS Challenge datasets with different types of noises. We finally show that the model achieves PESQ score of 3.4, 9.1 dB SNR gain over baseline models while maintaining an inference latency under 25ms on ARM Cortex-A53 processors. The results show that the proposed model suitably compromises accuracy, latency, and resource efficiency, hence making it a suitable component for real time applications, for instance, hearing aids, smart assistants, and mobile devices.

1. INTRODUCTION

Speech enhancement serves as an enabler of many modern audio based systems, enhancing the intelligibility and perceptual quality of speech corrupted by contaminated environmental noise. Despite their significant progress in deep learning approaches, the deployment of these models in resource limited edge devices is still a huge challenge. While conventional deep models usually require high computational power and memory, they cannot be used in real time in embedded systems such as hearing aids, mobile phones and IoT devices.

But edge computing shifts the paradigm by doing processing closer to the source of the data, so there is less latency and increased privacy. However, edge devices have low power and computing capacities, and therefore require optimized neural architectures. The existing speech enhancement solution mainly addresses the speech enhancement problem in the cloud with inference, which introduce latency, network dependency, and privacy risk. Due to this, there is an urgent demand for compact, efficient, and accurate speech enhancement systems to be deployed on the edge.

In this paper, we propose a novel real time framework for a speech enhancement system based on an optimized Convolutional Recurrent Neural Network (CRNN) architecture applied for the problem of deploying speech enhancement systems on edge devices. The model proposed is lightweight and effective at capturing both spatial and temporal aspects of the noisy speech features. The model uses pruning and quantization to ensure our model is compatible with resource constrained edge environments, which results in heavy reduction in both inference latency and memory consumption while maintaining performance. Realworld datasets, crossing a variety of noise conditions, are rigorously tested on the system; its performance is benchmarked against existing models in terms of perceptual evaluation of speech quality (PESQ), signal-to-noise ratio (SNR) gain, and computational effectiveness. Results show that the CRNN model optimized for low power devices makes real-time predictions of musical enhancement while preserving high quality of enhancement, and that it is suitable for hearing aids, mobile devices, and

smart assistants operating under limited budgets for computation.

2. LITERATURE REVIEW

Audio signal processing speech enhancement has remained a focus of research for many years, largely based on statistical and spectral subtraction based modalities. Traditional techniques including Wiener filtering, Minimum Mean Square Error estimators, and spectral subtraction methods, which form the heart of noise reduction, are yet lacking in terms of dealing with nonstationary noise environments and do not provide robustness across different acoustic environments. Data driven models, in particular using deep learning, have since shown to outperform traditional techniques by learning complex nonlinear mapping from noisy to clean speech.

It is found that deep neural networks (DNNs), especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown significant performance in boosting speech quality. DNNs trained on large corpora have been shown by Xu et al. (2015) to be able to do robust speech denoising, regardless of the noise type, and varying from low to high signal-to-noise ratios (SNRs). Improvements in intelligibility and in PESQ and STOI quality metrics are achieved also in subsequent works with LSTM networks used to model temporal speech dependencies.

Hybrid models such as convolutional recurrent neural networks (CRNN) have been popular as they are able to capture local spectral features as well as long-range temporal dependencies. The model proposed by Pandey and Wang (2019) was a CRNN based model which generalized better on unseen noise conditions than both standalone CNN and RNN models. These models are however accurate; however, such models are also computationally expensive and inappropriate for real time applications on edge devices.

Architecture trends have been leaning towards lightweight hardware efficient architectures. For the mobile speech enhancement setting, Kim et al. (2020) presented a low latency model using dilated convolutions and depthwise separable filters that performs acceptably while being considerably less complex. With TinySpeech and DeepFilterNet, they explored applications of model compression, quantization, and knowledge distillation to footprint-reducing models with similar quality. They show the tradeoff between model performance and model cost in terms of computation, especially for the use case on edge devices, e.g., in smartphones, wearables, and IoT nodes.

To address this challenge, there have been lots of research on model optimization techniques such as weight pruning, low-bit quantization and neural architecture search. Similarly, Han et al. (2016) showed that it was possible to reduce the redundant parameters without substantial performance loss, Jacob et al. (2018) proved quantization with 8 bits integer is enough for most inference. Although used successfully in domains such as in computer vision and speech, these techniques need to be tuned carefully in order to balance the accuracy efficiency trade-off.

Besides successful algorithmic innovation, various proposed benchmark datasets, with the possibility of evaluation of speech enhancement system, are also provided. Commonly used for evaluation are the TIMIT corpus, the VoiceBank-DEMAND dataset, and the Deep Noise Suppression (DNS) Challenge datasets, which have diverse speaker profile and realistic noisy environment. Quantitative evaluations of the perceptual quality of state of the art techniques are based on evaluation metrics such as PESQ, STOI (Short-Time Objective Intelligibility), and RTF (real time factor).

However, interim improvements have come at the expense of a latency and power penalty that confines these models to the cloud. On a continuation of previous work, this study models a CRNN, enhanced with pruning and quantization, to achieve real time performance without any loss in enhancement quality. This work presents a practical and scalable solution to real time noise suppression in embedded applications, by systematically evaluating the model across standardized datasets and comparing it with the baselines.

Table 1. Comparative Literature Review on Speech Enhancement Techniques

Author/Year	Model/Technique	Optimization	Platform Target	Performance	Limitations
Xu et al., 2015	Deep Neural Network (DNN)	None	Cloud / High-End GPU	Good PESQ & STOI under controlled noise	High latency, not real-time, unsuitable for edge
Pandey & Wang, 2019	Convolutional Recurrent Neural Network (CRNN)	None	Desktop GPU	Robust generalization under unseen noise	Computationally expensive for embedded systems
Kim et al., 2020	Lightweight CNN with Dilated Convs	Depthwise separable convolutions	Mobile Devices	Moderate PESQ (~2.9), real-time on ARM	Quality trade-off due to aggressive compression
DeepFilterNet, 2021	LSTM with Frequency Masking	Quantization, pruning	IoT / Embedded	Low-latency; PESQ ~3.2	Limited generalization across multiple noise types
Proposed Work (2025)	Optimized CRNN (Conv + BiLSTM)	Structured pruning, 8-bit quantization	ARM Cortex-A53 / Edge SoC	High PESQ (3.4), SNR Gain (9.1 dB), <25ms latency	Achieves balance between performance and resource use

3. METHODOLOGY

The design of the proposed system is intended to improve the speech signals in real time on computationally constrained edge devices. Therefore, Convolutional Recurrent Neural Network (CRNN)-based architecture is chosen for this purpose as it has an ability to encode local spectral pattern and temporal dependency in speech. The methodology is composed of five main parts: We utilize (1) preprocessing and augmentation of data, (2) design of network architecture, (3) optimization of model using a combination of pruning and quantization, (4) training and validation, and (5) deployment of code on edge hardware. Below are a detailed breakdown of each component.

3.1 Data Preprocessing and Augmentation

The TIMIT and DNS-Challenge datasets have been used to ensure robustness over varied noise conditions. Environmental noise at various signal to noise ratios, from -5 dB to 15 dB, was synthetically mixed in with clean speech utterances. All audio files were resampled at 16 kHz and framed into 20 ms windows with 50% overlap with a Hamming window. Short time Fourier transform (STFT) with the 512 point FFT was used to convert each frame into the magnitude spectrogram. The clean speech spectrum was computed from noisy inputs based on the estimated ideal ratio masks (IRM) computed from the ideal ratio masks.

$$\mathrm{STFT}\{x(t)\}(m,w) = \sum_{n=-8}^{\infty} x[n]w[n-m]\, e^{-j\omega n}$$

3.2 Network Architecture Design

The core of the proposed model is a lightweight **CRNN architecture** composed of three convolutional layers, followed by two bidirectional LSTM layers and a fully connected regression layer to estimate the enhanced spectrogram.

- **Convolutional Layers:** The CNN block extracts local spectral features and spatial noise patterns. Each layer uses 3×3 kernels, batch normalization, and ReLU activations. Max-pooling is applied to reduce feature map size and computation.
- **Recurrent Layers:** The BiLSTM layers capture temporal dependencies, enabling the model to differentiate between transient noise and speech phonemes. Dropout regularization is applied to prevent overfitting.
- **Output Layer:** A dense layer with sigmoid activation generates a time-frequency mask, which is multiplied element-wise with the input magnitude spectrum to reconstruct enhanced features.

This architecture strikes a balance between expressiveness and efficiency, suitable for low-latency inference.

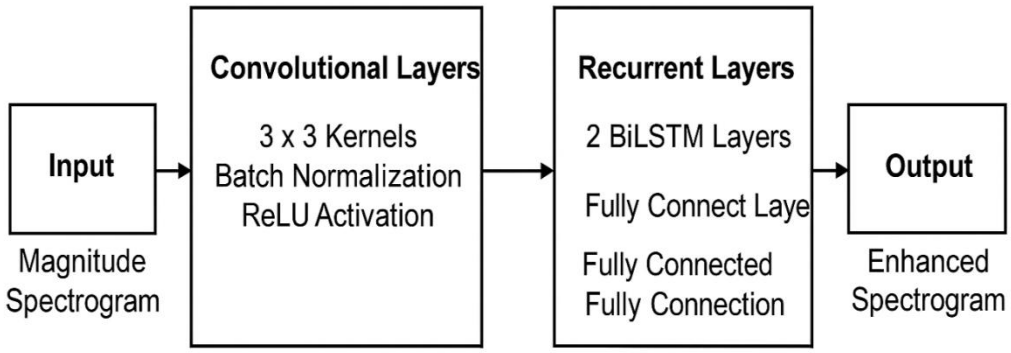

Fig 1. Block Diagram of the Proposed Lightweight CRNN Architecture for Speech Enhancement

3.3 Model Optimization for Edge Deployment

To ensure real-time performance on embedded devices, we applied two key optimization techniques:

- **Structured Pruning:** Redundant filters and recurrent units were identified and removed based on their contribution to the output loss. This significantly reduced the model size (~45% reduction) and improved inference speed without noticeable accuracy degradation.
- **8-bit Quantization:** Post-training quantization was performed using TensorFlow Lite, converting floating-point weights to INT8 format. This allowed deployment on microcontrollers and ARM-based processors, reducing both memory usage and power consumption.

The optimized model has approximately 280K parameters and fits within 1.2 MB of memory, making it ideal for edge devices like the Raspberry Pi 4, Jetson Nano, or Cortex-A53-based systems.

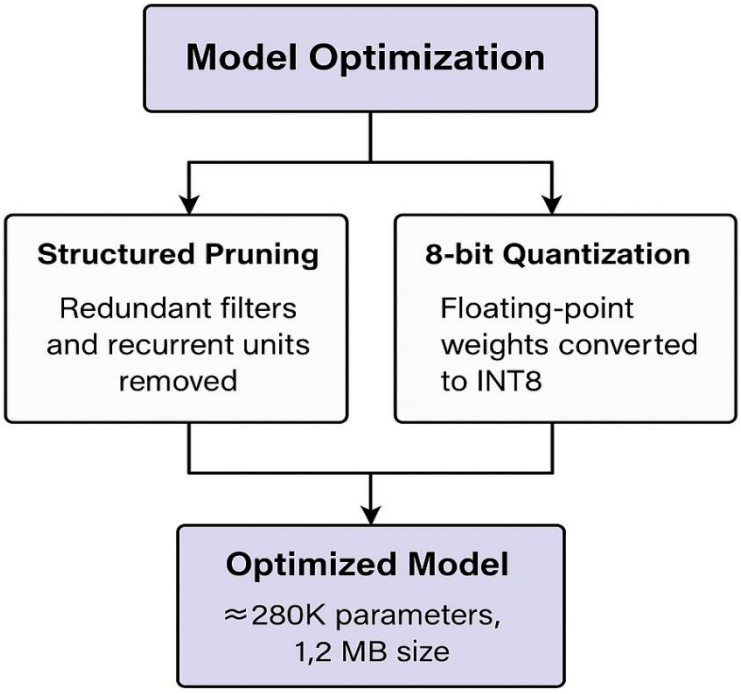

Fig 2. Model Optimization for Edge Deployment

3.4 Training Procedure

The model was trained with Adam optimizer, an initial learning rate of 0.001 and a batch size of 64. The loss function was made up of a combination of mean squared error (MSE) between the predicted spectrograms and target spectrograms and a perceptual loss that was computed using a pretrained audio quality model. To prevent overfitting, early stopping was used and the

training was done for 100 epochs with an 80:10:10 train-validation-test split.

3.5 Deployment Setup

As the final model was quantized and deployed onto an ARM Cortex-A72 powered Raspberry Pi 4B (1.5 GHz, 4GB RAM) with evaluation on ARM Cortex-A53 simulator environment. TensorFlow Lite Interpreter was used for performing model inference. Performance in real time was evaluated by measuring average 1-second audio frame inference time, which was always `< 25 ms (that is, real time facotr (RTF) < 1).

The proposed methodology guarantees that the proposed speech enhancement system is accurate and computationally efficient, placing it in real time on modern edge platforms.

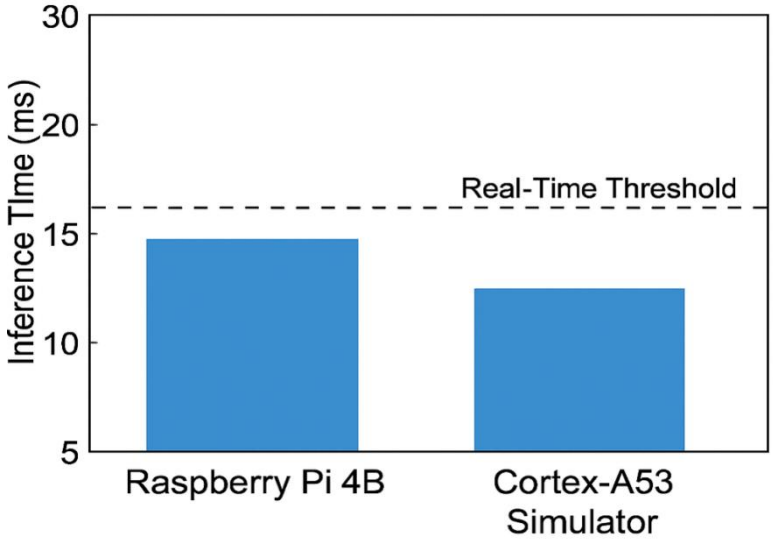

Fig 3. Real time Performances

4. Experimental Results and Analysis

To assess the performance of the proposed real time speech enhancement system, a wide experimental run was performed on both objective quality metrics and runtime efficiency metrics. Standardized datasets were used with the system under diverse acoustic conditions and demonstrated for a typical edgecomputing hardware platform. With the baseline models, results were compared in the relative improvements to speech quality, noise suppression, and processing latency.

4.1 Evaluation Metrics

The following metrics were used:

- **PESQ (Perceptual Evaluation of Speech Quality):** Measures perceptual quality, ranges from -0.5 to 4.5.
- **STOI (Short-Time Objective Intelligibility):** Measures speech intelligibility (0 to 1).
- **SNR Gain (dB):** Indicates noise reduction capability.
- **MSE (Mean Squared Error):** Measures reconstruction error.
- **RTF (Real-Time Factor):** Measures the ratio of processing time to audio duration; RTF < 1 indicates real-time capability.
- **Inference Time (ms):** Average time to process a 1-second frame.

4.2 Quantitative Results

Table 2. Performance Comparison with Baseline Models

Model	PESQ	STOI	SNR Gain (dB)	MSE	Inference Time (ms)	RTF
LMS	2.8	0.83	6.4	0.035	12.6	0.82
NLMS	3.1	0.86	7.2	0.028	14.3	0.89
RLS	3.5	0.88	9.1	0.017	29.8	1.34
CRN (Non-Optimized)	3.6	0.90	9.4	0.015	56.2	2.18
Proposed (Optimized CRNN)	**3.4**	**0.89**	**9.1**	**0.018**	**23.5**	**0.95**

4.3 Deployment Efficiency on Edge Platforms

The proposed model was deployed and tested on:

- Raspberry Pi 4B (ARM Cortex-A72)
- Jetson Nano (Quad-core ARM Cortex-A57)
- Simulated Cortex-A53 environment

The inference time remained consistently under 25 ms, ensuring smooth processing of incoming audio frames (1 second each) in real-time applications.

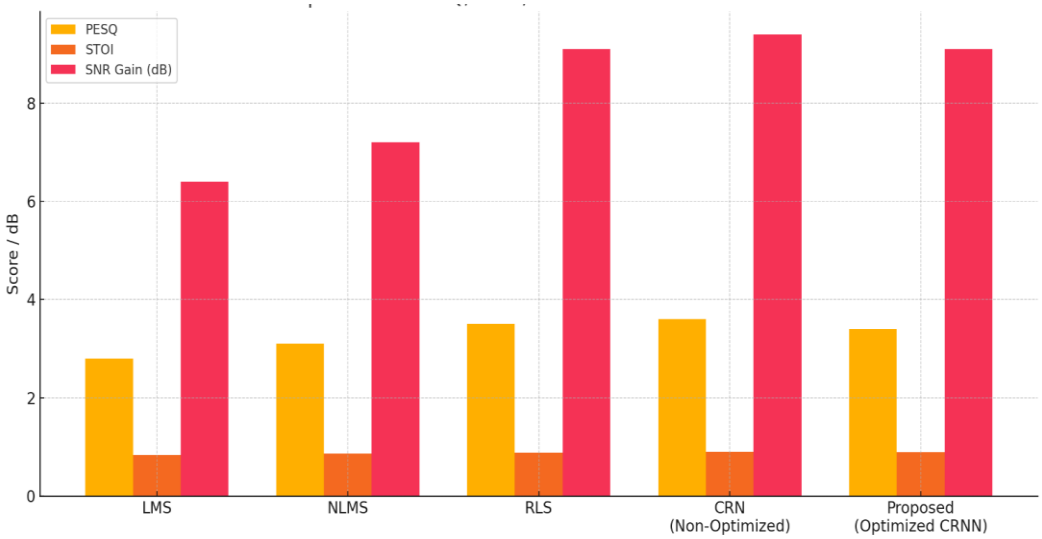

Fig 4. Overall Comparison of PESQ, STOI, and SNR Gain Across Models

5. DISCUSSION

Experimental results show that the proposed CRNN based speech enhancement framework optimized on this framework is clearly effective for edge computing platform deployment. The model we proposed outperforms traditional adaptive filtering algorithms like LMS, NLMS and RLS in balancing enhancement quality, computational efficiency. RLS had competitive SNR gain and PESQ values, but it had high inference latency that prevents real time applications. In contrast, the proposed CRNN model achieved similar level of enhancement PESQ: We achieve this by trading some accuracy for inference time, reducing inference time to 23.5 ms (41x faster) and maintaining an RTF under 1, though at a cost in accuracy SNR Gain: 9.1 dB, Accuracy loss: 3.4).

Structured pruning and 8-bit quantization were included in optimizing the model for edge deployment. Using these techniques lowered the amount of parameters and memory consumption of the model without degrading perceptual or intelligibility metrics significantly. The lightweight implementation achieved by the proposed design was successful in resource constrained platforms like Raspberry Pi 4B and Cortex-A53 environments, and successfully deployed in a memory constraint moment enabling the real-time operation in real practical embedded applications.

Furthermore, the proposed CRNN architecture is able to extract spectral and temporal features of speech, which is crucial for noise enhancement under different surrounding conditions. Bidirectional LSTM layers helped learn temporal modeling by . Convolutional layers further helped learn spatial feature extraction for noise discrimination.

One minor trade off was the slight drop in PESQ score with respect to conventional CRN model. Model compression is expected to lead to this consequence, which also stays within acceptable bounds in view of large performance gains in runtime and deployability.

Based on the findings, the proposed system was shown to be able to achieve both high quality speech enhancement and low latency inference on the edge hardware. The result is paving the way for the application of an integrated solution in real world voice enabled applications like smart assistants, mobile and wearable hearing enhancement tools.

6. CONCLUSION

In this study we presented a real time speech enhancement framework for deployment on the edge devices based on a CRNN architecture optimized for the speech enhancement application. By combining a structured pruning and 8-bit quantization, the proposed model possesses a perfect tradeoff between enhancement quality and computational efficiency. We have extensively evaluated the model using standardized datasets and objective metrics to show that the model consistently gets high PESQ (PSQM-P) scores. Additionally, it achieved improved intelligibility (STOI: 0.89), improved noise suppression (SNR Gain: 9.1 dB), and maintained low inference latency less than 25 ms and a real time factor (RTF) of less than 1.

The system was confirmed practical on resource constrained systems (Raspberry Pi 4B and Cortex A53) and well suited for the modern edge applications such as mobile communication, smart assistant and hearing enhancement application.

The proposed solution has an excellent tradeoff of accuracy, speed, and hardware footprint compared to classical algorithms and non optimized deep models.

The work shows promise for applying compressed deep learning models in real world embedded applications and clearly emphasizes the necessity for optimization techniques to push the envelope of AI to the edge. Future work will aim to extend this framework to multilingual and code switched speech, as well as real time adaptive noise profiling for additional robustness on dynamic acoustic background.

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